A Hybrid Discrete Choice Model of Differentiated Product Demand with An Application to Personal Computers

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Abstract

In this paper I consider a new discrete choice model of differentiated product demand that describes markets where product groups are horizontally differentiated while products of a given group are vertically differentiated conditional on product characteristics. I distinguish the two types of differentiation by putting an idiosyncratic taste shock only at a group level so that all products within a group share the same shock. As a result, the model combines the pure characteristics demand model of Berry and Pakes (2007) and the random coefficient logit demand model of Berry, Levinsohn, and Pakes (1995). I compare this hybrid model with the other two demand models using product-level data on personal computers. I also show how demand estimates can be used to analyze product repositioning in the post-merger market.

Keywords: Discrete choice models, product differentiation, personal computer market, post-merger analysis

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1 Introduction

Consider a market where brands compete with multiple products, and products of a given brand are vertically differentiated. The auto market is a good example. There are different brands of cars, and each brand has a low end economy car and a high end luxurious car. The computer market is another example. Products of each brand are ranged from computers of a low CPU speed with low memory and hard disk capacities to computers of a high CPU speed with high memory and hard disk capacities. Products of the same brand are not necessarily vertically differentiated on the single dimension. For example, it is not straightforward to compare SUVs with sports cars on the single quality dimension. However, conditional on some characteristics, for example the car size in this case, consumers have conditional consensus on quality ranking.

In this paper I consider a new discrete choice model of differentiated product demand in which product groups are horizontally differentiated while products of a given group are vertically differentiated conditional on product characteristics. I call a product group that contains vertically differentiated products a brand. This is consistent with the role of brands found in many markets, but the model can be applied to any product groups containing products that are vertically differentiated conditional on product characteristics.

I distinguish these two types of differentiation using an taste shock. I assume that consumers receive the taste shock only at a brand level so that all products within a brand share the same shock. This shock represents each consumer's "taste" for a brand that is not captured by observed and unobserved product characteristics, and I assume that it is distributed i.i.d. with a Type I extreme-value distribution. As a result, consumers are uncertain about which brand to choose, but they know for sure which product to choose within each brand and their within-brand product choice is solely determined by their preference for product characteristics.

I call this model a hybrid model because it resembles the random coefficient logit demand model in describing a brand choice (Berry, Levinsohn, and Pakes 1995, BLP hereafter) and the pure characteristics demand model in describing a within-brand product choice (Berry and Pakes 2007, PCM hereafter). In particular, the market share function of product j_k of brand k can be written as the product of the probability that brand k is chosen and the probability that product j_k is chosen given that brand k is chosen. The former probability is similar to the choice probability in BLP, and the latter to that of the PCM.

This hybrid model identifies preference for product characteristics in a similar way as the PCM. Consider the one random coefficient PCM and suppose there is one observed characteristic and all unobserved characteristics can be summarized on the single dimension. If more expensive products have more of the observed characteristic, the model identifies this characteristic as a desirable characteristic. The main difference is that the hybrid model compares products of each brand on the quality ladder separately, while the PCM compares all products on it at the same time. With two random coefficients the hybrid model compares products of each brand in the two-dimensional quality space, while the PCM compares all products in the same quality space at the same time. Thus, the quality space is much less crowded in the hybrid model.

One may view the hybrid model as an extension of the PCM with random coefficients on the brand dummy variables. But by using the Type I extreme-value distributional assumption I avoid the computational burden that limits the number of the random coefficients used in its applications. Also, this assumption connects the hybrid model to BLP that has been widely used in the industrial organization and marketing literature (Nevo 2001; Petrin 2002, and many others). If one focuses on brand choices, the hybrid model is not much different from BLP. Thus, one may also view the hybrid model as an extension of BLP with more micro-level product choices accounted for.

One should note that my hybrid model is different from the nested logit model. The two models are similar in that the market share function is the product of the group choice probability and the individual product choice probability. However, in the nested logit model the former probability is determined by the average value the consumer receives from choosing a group. On the other hand, in the hybrid model each consumer has a different group or brand choice probability and it is determined by a product that maximizes her utility within each group. In other words, there is one product in each group that maximizes a consumer's utility, and she compares these products in comparing brands. Also, while grouping is arbitrary in the nested logit model, the hybrid model requires that each group should have a vertical structure in it.

The hybrid model distinguishes two types of cross substitutions: the within-brand substitution and the between-brand substitution. The former is confined to products of the same brand and has the same substitution pattern as in the PCM. The latter determines the substitution pattern for products of different brands and has a similar pattern as in BLP but with a distinct difference. That is, impact of a price change on other brands is confined to products of similar quality. As a result, a product has more substitutes than in the PCM, but fewer substitutes than in BLP. The hybrid model also distinguishes brand entry from product entry. New products introduced by existing brands affect consumer welfare differently from new products introduced by new brands. Note that both BLP and the PCM do not distinguish between the two.

I compare the hybrid model with BLP and the PCM using monthly product-level data on personal computers (PCs) from October 2001 to September 2004. The data set covers about 60 percent of PCs sold at U.S. retail stores. Price, sales in unit, and detailed product characteristics are available at a UPC bar code level. There are six brands present in the data, and they are Sony, Hewlett-Packard (HP hereafter), Gateway, Compaq, eMachines and Apple.

Previous studies on PC demand use BLP-type models with much more aggregate data. For example, Chu, Chintagunta and Vilcassim (2007) define a desktop PC as a brand-model-CPU type combination. Goeree (2008) defines it as a brand-model-CPU type-CPU speed combination. These data formats eliminate the vertical structure within brands such that products are presented much more horizontally differentiated than they actually are.

An exception is Bajari and Benkard (2005) who use the same product-level data I use here. Their model is similar to the PCM in that it does not have the idiosyncratic taste shock, but more flexible in a sense that they do not make any distributional assumption on the random coefficient for product characteristics. However, they only set-identify preference and demand because of discrete product characteristics. Also, their demand estimates cannot be used to learn about supply-side parameters like the marginal cost and markup.

Estimation results show that almost all product characteristics have statistically significant coefficients and they have expected signs in both the hybrid model and the PCM. On the other hand, only three out of ten are statistically significant in BLP. One of them is the level 2 cache variable. This variable indicates whether computers have low-end CPUs like Celeron processors. In BLP it has a positive coefficient, implying misleadingly that consumers prefer a computer with the low-end CPU if all other characteristics and price are the same. This does not happen in the other two models because they treat cheaper products as lower quality products.

Despite the statistical significance, the consumer's willingness to pay for quality improvement is unrealistically low in the PCM. For example, the average consumer is willing to pay about \$30 for increasing CPU speed by 1 GHz. This is much smaller than an extra money needed to have a 1 GHz faster CPU. This low magnitude is a result of having the quality space "too crowded" with products. On the other hand, the average consumer's willingness to pay for the same CPU speed difference is about $200 in the hybrid model. Also, it becomes hard to identify preference with the PCM as the market size increases. This happens because all products are pushed to one side of the distribution so that only local information on the distribution is provided.

Lastly, I show how demand estimates can be used to analyze product repositioning in the post-merger market. Using the demand estimates in the hybrid model I construct a quality index for each brand. This index is a linear function of observed product characteristics with each characteristics weighted by the estimated marginal utility. Having a correct sign for product characteristics is important in correctly projecting products on characteristics space.

The merger between HP and Compaq took place in February 2002, and my data set covers periods before and after their merger. Markup recovered by the demand estimates shows that Compaq's profit increased over time while HP's profit gradually decreased. However, Compaq's average price went down further than HP's average price. This asymmetry suggests that Compaq's increased markup is not necessarily evidence of less competitive market structure.

The quality index shows that this post-merger market trend is associated with product repositioning. Compaq's quality index improves more slowly than that of HP such that their difference becomes increasingly larger over time. Moreover, Compaq's index becomes almost identical to eMachines' index from July 2003, suggesting that Compaq now competes with eMachines at the low-end of the market.

The rest of the paper is organized as follows. Section 2 describes the hybrid demand model. Section 3 estimates demand for PCs using BLP, the PCM and the hybrid model and compares results. Section 4 analyzes the post-merger PC market. Section 5 concludes.

2 Hybrid Demand Model

2.1 Utility Function

Suppose there are $t = 1, 2, ..., T$ markets with K brands. Each brand has J_k products that are vertically differentiated. Products of the same brand are not necessarily vertically differentiated. The model can easily be extended by adding more random coefficients, but I will confine my exposition to the simplest case. Each market has $i = 1, 2, ..., I_t$ consumers. Given a market, the indirect utility of consumer i from product j of brand k is

$$u_{ij_k} = \delta_{j_k} - \alpha_i p_{j_k} + \varepsilon_{ik}, \quad \text{for } 1 \leq j_k \leq J_k \text{ and } 1 \leq k \leq K \tag{1}$$

where δ_{j_k} and p_{j_k} are quality and price of product j of brand k respectively, α_i is the individual-specific price coefficient with $\alpha_i \sim F(\theta)$, and ε_{ik} is consumer $i's$ idiosyncratic preference for brand k which is assumed to be an *i.i.d.* Type I extreme-value random variable. Note that ε_{ik} is independently and identically distributed across consumers and brands, but not across products of the same brand. In other words, consumers receive an idiosyncratic taste shock when they choose brands, but once they choose brands they have the same shock for products of the same brand. This is a key difference that distinguishes this model from other discrete choice models.

I assume that product quality δ_{j_k} is a linear function of product characteristics so that

$$\delta_{j_k} = \mathbf{x}_{j_k}\boldsymbol{\beta} + \xi_{j_k}$$

where $\mathbf{x}_{j_k}$ is a vector of observable characteristics of product j of brand k, $\boldsymbol{\beta}$ represents a marginal utility that a consumer derives from product characteristics, and ξ_{j_k} is the mean quality of characteristics that the consumer observes but the econometrician does not. Heterogeneity in consumer preferences over observable characteristics can be modelled by letting a subset of $\boldsymbol{\beta}$ be random variables.

2.2 Market Share

A rational consumer with a value of α_i chooses brand k over other brands if and only if

$$\max_{j_k \in k} \left(\delta_{j_k} - \alpha_i p_{j_k} \right) + \varepsilon_{ik} > \max_{j_r \in r} \left(\delta_{j_r} - \alpha_i p_{j_r} \right) + \varepsilon_{ir}, \quad \forall r \neq k.$$

Within brand k consumer i chooses product j if and only if

$$\delta_{j_k} - \alpha_i p_{j_k} > \delta_{h_k} - a_i p_{h_k}, \quad \forall h_k \neq j_k.$$

Thus the probability of brand k being chosen is

$$\Pr \left(\text{brand } k \text{ being chosen} \right) = \int \frac{\exp \left(\max_{j_k \in k} \left(\delta_{j_k} - \alpha_i p_{j_k} \right) \right)}{\sum_{r=1}^{K} \exp \left(\max_{j_r \in r} \left(\delta_{j_r} - \alpha_i p_{j_r} \right) \right)} f \left(\alpha \right) d\alpha, \tag{2}$$

and the probability of product j being chosen conditional on brand k being chosen is

$$\Pr \left(j \text{ being chosen } | k \text{ being chosen} \right) = F \left(\overline{\triangle}_{j_k} \left(\delta_k, p_k \right) | \boldsymbol{\theta} \right) - F \left(\underline{\triangle}_{j_k} \left(\delta_k, p_k \right) | \boldsymbol{\theta} \right), \tag{3}$$

where $F(.)$ is the *cdf* of α_i, $\overline{\triangle}_j(\delta_k, p_k) = \frac{\delta_{j_k} - \delta_{j-1_k}}{p_{j_k} - p_{j-1_k}}$, and $\underline{\triangle}_{j_k}(\delta_k, p_k) = \frac{\delta_{j+1_k} - \delta_{j_k}}{p_{j+1_k} - p_{j_k}}$ with products in each brand sorted in the order of ascending price. Note that the probability of the brand choice also depends on the consumer's product choice within each brand through a max function.

The market share of product j of brand k is

$$s_{j_k} = \int_{\alpha_i \in j_k} \frac{\exp(\delta_{j_k} - \alpha_i p_{j_k})}{\sum_{r=1}^{K} \exp(\max_{j_r \in r}(\delta_{j_r} - \alpha_i p_{j_r}))} f(\alpha)\, d\alpha$$

where $\alpha_i \in j_k$ indicates consumers who choose product j in brand k. Note that there is no max function in the numerator in the second term. This share function can be rewritten as the product of the probability in equation (3) and the probability that brand k is chosen by those consumers who buy product j of brand k. That is,

$$s_{j_k} = \left[F\left(\overline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right) - F\left(\underline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right)\right] \int_{\alpha_i \in j_k} \frac{\exp(\delta_{j_k} - \alpha_i p_{j_k})}{\sum_{r=1}^{K} \exp(\max_{j_r \in r}(\delta_{j_r} - \alpha_i p_{j_r}))} g(\alpha)\, d\alpha \tag{4}$$

where

$$g(\alpha) = \frac{f(\alpha)}{\left[F\left(\overline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right) - F\left(\underline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right)\right]},$$

and its numerical approximation is

$$\widetilde{s}_{j_k} = \left[F\left(\overline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right) - F\left(\underline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right)\right] \frac{1}{ns} \sum_{i \in j_k} \frac{\exp(\delta_{j_k} - \alpha_i p_{j_k})}{\sum_{r=1}^{K} \exp(\max_{j_r \in r}(\delta_{j_r} - \alpha_i p_{j_r}))},$$

where ns is the number of simulated consumers whose $\alpha \in \left[F\left(\overline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right), F\left(\underline{\triangle}_{j_k}(\delta_k, p_k)\,|\boldsymbol{\theta}\right)\right)$. The market share function shows why the model is a hybrid model. By limiting the idiosyncratic taste shock at a brand choice level, the model combines the choice probabilities of the PCM and

BLP.

The random coefficients capture consumers' heterogenous preference on product characteristics. In this particular model, a value of α_i determines which product to choose within each brand. A consumer with a low value of α_i chooses a high quality product (almost equivalently, an expensive product) within brands and a consumer with a high value chooses a low quality product. Then she compares these products in comparing brands. Thus, the probability of choosing a certain brand is always positive and a function of its product that maximizes her utility.

This model accommodates two types of the outside option. One is to choose the lowest quality product in each brand, and its value is set to zero. Consumers whose α_i is very high choose this outside option. This is the same outside option used in the PCM. In practice, it represents a difference between a "true" brand-level sale (usually reported by firms or industry reports) and a sample brand-level sale shown in data.[1]

The other outside option is to choose brands that are not included in the sample or not to choose any products, and its market share is determined by the market definition. Instead of setting its value to zero, it can be excluded as in equation (4) or its value can be estimated if included. When included, the denominator inside the integral in equation (4) becomes

$$\exp(\delta_0) + \sum_{r=1}^{K} \exp\left(\max_{j_r \in r} \left(\delta_{j_r} - \alpha_i p_{j_r} \right) \right),$$

where δ_0 is estimated. For example, my data set on PCs does not include Dell products as they were collected from retail stores. Instead of ignoring them, I include it in the outside option and

[1] It is very possible that it can include high-end products that are dropped from the sample because of tiny market shares or not included in the sample in a data collection process. If included, this may affect adjacent products' price elasticities, but will not affect coefficients on product characteristics significantly.

estimate the average value of choosing Dell products. More details are provided in section 3.2.

2.3 Price Elasticity

The own price elasticity is

$$\begin{aligned}
\frac{\partial s_{j_k}}{\partial p_{j_k}}\frac{p_{j_k}}{s_{j_k}} &= \frac{p_{j_k}}{s_{j_k}}\frac{\partial}{\partial p_{j_k}}\left(\int_{\alpha_i\in j_k}\frac{\exp\left(\delta_{j_k}-\alpha_i p_{j_k}\right)}{\sum_{r=1}^{K}\exp\left(\max_{j_r\in r}\left(\delta_{j_r}-\alpha_i p_{j_r}\right)\right)}f\left(\alpha\right)d\alpha\right) \\
&= \frac{p_{j_k}}{s_{j_k}}\left(\Psi\left(\overline{\triangle}_{j_k}\right)f\left(\overline{\triangle}_{j_k}|\boldsymbol{\theta}\right)\frac{\partial\overline{\triangle}_{j_k}}{\partial p_{j_k}}-\Psi\left(\underline{\triangle}_{j_k}\right)f\left(\underline{\triangle}_{j_k}|\boldsymbol{\theta}\right)\frac{\partial\underline{\triangle}_{j_k}}{\partial p_{j_k}}\right) \\
&\quad +\frac{p_{j_k}}{s_{j_k}}\left(\int_{\alpha_i\in j_k}-\alpha_i\Psi\left(\alpha_i\right)\left(1-\Psi\left(\alpha_i\right)\right)f\left(\alpha\right)d\alpha\right) \qquad (5)
\end{aligned}$$

where

$$\Psi\left(\alpha_i\right)=\frac{\exp\left(\delta_{j_k}-\alpha_i p_{j_k}\right)}{\sum_{r=1}^{K}\exp\left(\max_{j_r\in r}\left(\delta_{j_r}-\alpha_i p_{j_r}\right)\right)}.$$

Equation (5) shows that the own price elasticity equation consists of two parts. The term in the first bracket captures changes in market share due to substitution among products of the same brand, and the term in the second bracket captures changes due to substitution across brands. The former resembles the own elasticity in the PCM, but is a function of products of the same brand and is weighted by $\Psi\left(\overline{\triangle}_{j_k}\right)$ and $\Psi\left(\underline{\triangle}_{j_k}\right)$. The latter resembles the own elasticity in BLP, but only a subset of consumers is considered such that $-\alpha_i\Psi\left(\alpha_i\right)\left(1-\Psi\left(\alpha_i\right)\right)$ is integrated over consumers who buy product j given brand k.

There are two types of cross price elasticity: within-brand cross elasticity and between-brand cross elasticity. The within-brand cross elasticity measures impact of price changes on the same brand products, and the between-brand cross elasticity measures impact of price changes on products of different brands. The former is defined as

$$\begin{aligned}\frac{\partial s_{j_k}}{\partial p_{h_k}}\frac{p_{h_k}}{s_{j_k}} &= \frac{p_{h_k}}{s_{j_k}}\frac{\partial}{\partial p_{h_k}}\left(\int_{\alpha_i \in j_k}\frac{\exp\left(\delta_{j_k}-\alpha_i p_{j_k}\right)}{\sum_{r=1}^{K}\exp\left(\max_{j_r\in r}\left(\delta_{j_r}-\alpha_i p_{j_r}\right)\right)}f\left(\alpha\right)d\alpha\right)\\ &= \frac{p_{h_k}}{s_{j_k}}\left(\Psi\left(\overline{\triangle}_{j_k}\right)f\left(\overline{\triangle}_{j_k}|\boldsymbol{\theta}\right)\frac{\partial\overline{\triangle}_{j_k}}{\partial p_{h_k}}-\Psi\left(\underline{\triangle}_{j_k}\right)f\left(\underline{\triangle}_{j_k}|\boldsymbol{\theta}\right)\frac{\partial\underline{\triangle}_{j_k}}{\partial p_{h_k}}\right),\end{aligned}\tag{6}$$

where $\partial\overline{\triangle}_{j_k}/\partial p_{h_k}$ $\left(\text{or } \partial\underline{\triangle}_{j_k}/\partial p_{h_k}\right)$ is zero if $\overline{\triangle}_{j_k}$ $\left(\text{or } \underline{\triangle}_{j_k}\right)$ is not a function of p_{h_k}. The latter cross elasticity is defined as

$$\frac{\partial s_{j_k}}{\partial p_{h_m}}\frac{p_{h_m}}{s_{j_k}} = \frac{p_{h_m}}{s_{j_k}}\left(\int_{\alpha_i \in j_k}\frac{\alpha_i\exp\left(\delta_{j_k}-\alpha_i p_{j_k}\right)\exp\left(\delta_{h_m}-\alpha_i p_{h_m}\right)}{\left[\sum_{r=1}^{K}\exp\left(\max_{j_r\in r}\left(\delta_{j_r}-\alpha_i p_{j_r}\right)\right)\right]^2}f\left(\alpha\right)d\alpha\right)\tag{7}$$

if $\left(\delta_{h_m}-\alpha_i p_{h_m}\right)=\arg\max_{j_m}\left(\delta_{j_m}-\alpha_i p_{j_m}\right)$ for $\alpha_i \in j_k$. If not, $\partial s_{j_k}/\partial p_{h_m}=0$.

Equations (6) and (7) show that when a price of a given product changes it affects products of the same brand in its adjacent neighborhood as well as products of different brands with similar quality. This is an important difference from other discrete choice models. For example, in the PCM with one random coefficient a price change only affects products in a given product's adjacent neighborhood. In any sorts of the logit demand model, it affects all other products in the market.

2.4 Consumer Welfare

Consumer welfare of a consumer with a value of α_i, converted into a monetary unit, is given as

$$\frac{\ln\left(\sum_{k=1}^{K}\exp\left(\max_{j_k\in k}\left(\delta_{j_k}-\alpha_i p_{j_k}\right)\right)\right)}{\alpha_i}.\tag{8}$$

The summation in the numerator is over brands, not over all products in the market, and there is a max function inside the exponential function. The model links the consumer to a product in each brand that maximizes her utility, and computes her welfare over products of her choice in each brand. The average consumer welfare is given as

$$\int \frac{\ln\left(\sum_{k=1}^{K} \exp\left(\max_{j_k \in k}\left(\delta_{j_k} - \alpha_i p_{j_k}\right)\right)\right)}{\alpha_i} dF\left(\alpha\right) \tag{9}$$

Note that, as a value of α_i changes, a product choice within brands also changes by the max function. Equation (9) shows that, given a consumer distribution $F\left(\alpha\right)$, consumer welfare in the hybrid model is likely to be smaller than consumer welfare in BLP where the summation in the numerator is over all products. It also shows that it is likely to be higher than in the PCM where there is no summation in the numerator.

2.5 Estimation

An estimation procedure is similar to that of BLP or the PCM. Given parameter values, it finds product quality $\boldsymbol{\delta}$ such that the model predicted market shares are equal to real market shares. Then it computes a GMM objective function based on moment conditions that the mean of unobserved characteristics is uncorrelated with instrumental variables. By repeating this for different parameter values, it searches for values that minimize the GMM objective function. Parameters to be identified include coefficients on product characteristics and parameters of the distribution of α.

A key difference is in finding product quality $\boldsymbol{\delta}$ that matches the model predicted market shares with real market shares. The contraction mapping in BLP is not appropriate because a market share is a function of a subset of products. The method used in the one random coefficient PCM cannot be used, because the share function in equation (4) is not invertible. The search algorithm for the multiple random coefficient PCM is not appropriate either, because it uses the contraction mapping to obtain a starting point.

Newton-Raphson method is a natural candidate for this type of problems. It finds roots for a system of nonlinear equations. There are $\sum_{k=1}^{K} J_k$ nonlinear equations, which are the model predicted share equations minus observed market shares, and $\sum_{k=1}^{K} J_k$ variables, a vector of product quality. This method works well with any starting values when the number of products per market is up to twenty. As the number of products goes higher than twenty, having good starting values becomes critical. However, when there are more than fifty products per market, the computational time increases so much that it becomes an impractical method.

For markets with more than fifty products, I consider a more practical yet theoretically valid method. The main idea is to use observed within-brand shares to approximate the conditional probability of choosing a product within a brand. The same idea is used in Berry (1994) in estimating the nested logit demand model.

This method consists of two steps. In the first step, quality of the lowest quality product, other than the outside option, in each brand is set to an arbitrary value, and quality of the other products is computed by equating (observed) within-brand shares to equation (3). In the second step, the quality of the lowest quality product in each brand is found by equating observed brand shares to equation (2). The first step is the same procedure used in the PCM. The second step is Newton-Raphson method with the number of roots equal to the number of brands.

In the one random coefficient hybrid model, the computational burden is negligible in the first step as product quality can be easily computed by inverting equation (3). The second step takes longer, but the computational burden is rarely prohibitive as the number of brands is almost always far smaller than the number of products.

The GMM estimator in the one random coefficient hybrid model belongs to the class of estimators that Berry, Linton, and Pakes (2004) consider. The share function in equation (4) satisfies their regularity conditions, and the share function simulator is the same as theirs. Therefore, their results on the consistency and the asymptotic normality (Theorems 1 and 2) can be applied directly. Berry *et.al.* (2004) do not formally provide asymptotic properties for the multi-dimensional pure characteristics model. Instead, they explain why it is not likely to differ from the unidimensional model, and support their argument with Monte Carlo simulations. I expect the multi-dimensional hybrid model to share the same asymptotic properties as the multi-dimensional pure characteristics model, but leave a formal proof for future research.

3 Comparison with Other Models

3.1 Data and Industry

Scanner data on desktop PCs are used for demand estimation. The data are collected from US retail stores by NPD Techworld, a private consulting firm specialized in information technology. So, I estimate household demand for desktop PCs. I exclude laptops from the data to use the one random coefficient model, but they can be included by putting another random coefficient on the PC format.

The data include revenue, quantity sold, and product characteristics. I calculated the average price by dividing revenue by quantity sold. The sample period starts from October 2001 and ends in September 2004, and observations are on a monthly basis. Product characteristics include CPU speed, CPU type (Intel, AMD, or Apple), memory capacity, hard drive capacity, the size of the level 2 cache, the screen size, whether the screen is LCD, whether the DVD reader is included, and whether the DVD writer is included. I select observations with more than 1,000 units of sale, and they cover about 90% of the total sale. My sample consists of 534 products and 1,875 observations for 36 months.[2] There are six brands in the sample, and they are Sony, HP, Gateway, Compaq, eMachines, and Apple. Dell is not included as it sells only through the internet. However, I include Dell's presence in my demand model and use its aggregate market share in demand estimation. Details are in the next section.

Summary statistics are reported in Tables 1, A-1, and A-2. I averaged all variables weighted by quantity at a monthly level, and then averaged at a quarterly level for the table presentation. The tables show a well known trend of the PC industry. Product attributes improve over time without a significant price increase. The average CPU speed increased from 1.2 GHz to 2.48 GHz, the average memory capacity from 232.78 MB to 445.36 MB, the average hard drive capacity from 42.29 GB to 113.17 GB, the proportion of computers with a DVD reader from 0.51 to 0.93, and the proportion of computers with a DVD writer from 0.02 to 0.44. However, the average price decreased from $825.88 to $690.64. The average and total sales follow a seasonal cycle with the fourth quarter of each year showing stronger demand than the other three quarters.

Figure 1 shows a brand level (within) market share during the sample period. I do not have product level data on Dell, but used an industry report to recover its brand level share. The figure shows that HP's market share decreased from 27 percent to 16 percent over time, while Compaq's share increased from 12 percent to 16 percent. Note that HP and Compaq were merged in February of 2001. The merged firm's total share sharply decreased from 40 percent to 30 percent in six months after the merger but fluctuated around 30 percent afterwards. Dell and eMachines both gained market share during the sample period, while Sony lost its share. Apple's market share rarely exceeded one percent for the entire sample period. At the end of the sample period,

[2] See the appendix for details of the data.

HP, Compaq and eMachines have very similar market shares. All brands' total sale did not change much after the first quarter of 2002, so one can infer that most consumers HP lost switched to other brands like Compaq, eMachines and Dell.

Figure 2 shows a brand level average price during the sample period. I take the simple average across products instead of using sales as a weight. All brands do not follow the same price trend. HP's average price fluctuated between \$800 and \$1,000 and Apple's average price fluctuated around \$1,500. eMachines' average price did not change significantly. But Compaq's average price went down from \$900 to \$600 and Sony's average price went up from below \$1,200 to \$1,400. Most interestingly, the price gap between HP and Compaq becomes widened over time. It is less than \$100 right before the merger, but becomes wider and reaches about \$300 by the end of the sample period.

These figures suggest that the merged firm did not necessarily benefit from the merger. It did not gain market share, nor raised prices. Compaq's increased market share seems to be a result of the decreasing price, but its impact on the firm's profit is unclear without markup being recovered. Also, a source of Compaq's price decline is unclear. It can be due to a decreasing marginal cost or product repositioning. Once consumer demand is estimated, I can answer this question.

3.2 Market Size and Outside Options

I consider two types of the market in my estimation. One is the US household desktop computer market, and its size is based on the number of computers sold to household consumers. According to IDC, a research company specialized in information technology, about 17.1 million computers were sold to household consumers in 2002 and about 20 millions in 2003. Based on these numbers

I estimate the monthly market size, accounting for seasonality. The mean size per month is about 1.4 millions. I also estimate the total monthly sale of Dell computers. The second type of the market is a potential household computer market in the US and it includes all potential consumers who consider buying computers. I choose three sizes: 3 millions, 5 millions and 10 millions.

I consider three outside options based on the two markets defined above. The first is to buy products that belong to the six brands in my sample but do not appear in the sample. These are the outside options within each brand, and I assume that consumers receive the lowest utility from these products and set their values to zero. Thus, consumers with high values of α are likely to choose these products. To compute its market share I first recover each brand's sale of products that do not appear in the sample using the brand level market share estimated by industry reports, and divide it by the market size I define. For example, if brand A's total market share is estimated to be 30%, its total sale will be 30% of the US household desktop computer market size. Then the sale of its products that do not appear in my data is the difference between the estimated total sale and its sale in my sample. The second outside option is to buy Dell products, and the third option is to make no purchase. I include the first two outside options when I use the first type of the market, and include all three options with the second type.

With the three outside options the denominator inside the integral in equation (4) becomes

$$\exp\left(\delta_{Dell}\right) + \exp\left(\delta_0\right) + \sum_{r=1}^{K} \exp\left(\max_{j_r \in r}\left(\delta_{j_r} - \alpha_i p_{j_r}\right)\right), \tag{10}$$

where δ_{Dell} and δ_0 are the average value of choosing Dell products and the average value of making no purchase respectively. These two values are estimated.[3]

[3] The third type of the outside option represents consumers who actively search for personal computers but do not buy any products. This group may play an important role in determining a price trend over time. However,

Note that in both BLP and the PCM there is only one outside option. In BLP the outside option enters in the denominator of its share function and its value is set to zero. In the PCM the outside option is similar to the first outside option described above, and its value is also set to zero.

3.3 Demand Estimates

I first estimate demand using the four logit models and the PCM. The four logit models are the OLS logit, the IV logit, and two versions of BLP. The firm dummy and the time dummy variables are included in all models in addition to the observed characteristics. Demand estimates are reported in Table 2. Except for the OLS logit model, I use the BLP-type instrumental variables interacted with the month dummy variables as instrumental variables. Characteristics used for these instrumental variables are the CPU speed, the memory capacity, and the screen size. The interaction with the time dummy variable accounts for technological advance that reduces production costs over time. Demand estimates with other instrumental variables are reported in Table B-1 in the appendix.

The first two columns in Table 2 show that the price variable is positively correlated with unobservable characteristics and that the instrumental variables mitigate this problem. However, only three product characteristics have significant coefficients (CPU speed, DVD writer, smaller cache size) and the smaller cache variable has a positive sign, misleadingly suggesting that consumers prefer products with a smaller cache size.

The third and the fourth columns report demand estimates in BLP. The price coefficient is distributed normal in the third column (BLP I) and distributed log normal in the fourth (BLP II). The price coefficient is not significant, and other estimates are not statistically significant either.

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a dynamic model is required to treat this aspect properly and it is beyond the scope of this paper to consider this aspect. Thus I assume that consumption behavior is static.

Tables B-2 and B-3 in the appendix report BLP estimates in different specifications, and those estimates are not very different from those in Table 2.

The last column reports demand estimates in the PCM. The US household desktop computer market excluding Dell products is used as the market because the model collapses as the market size approaches to 2 millions.[4] All coefficients on product characteristics are significant at a 5% level. The smaller cache variable coefficient has a negative sign, correctly suggesting that consumers prefer products with a larger cache size. Intel and AMD CPU have negative coefficients, suggesting that consumers prefer Apple computer CPUs.

The estimates imply that consumers' willingness to pay for improved characteristics is relatively small in the PCM. For example, the average consumer is willing to pay $30 more for a 1 GHz faster CPU. The top 10% consumers are willing to pay $320 more. In BLP I the average consumer is willing to pay $318 more. The top 10% are willing to pay $466 more for the same improvement.

Table 3 reports demand estimates in the hybrid model. The price coefficient is distributed log normal with the log mean set to zero. In the first column the market is defined as the US household desktop computer market. In the second to the fourth columns the market includes potential consumers, and its size is set to three millions, five millions and ten millions respectively.

All coefficients except for the coefficient of the memory variable are significant at a 5% level, and the signs of the coefficients are reasonable. All "desirable" characteristics like CPU Speed, Hard Drive, Screen Size, etc. have positive coefficients. Consumers prefer the DVD writer as much as a 1 GHz faster CPU. The small cache, the Intel CPU, and the AMD CPU variables

[4] In the logit model a larger market size does not change estimates except for the constant term. In the vertical model magnitudes of estimates decrease as the market size increases.

have negative coefficients as in the PCM. The average consumer is willing to pay $130 more for a 1 GHz faster CPU. The top 10% are willing to pay $220 more.

Interestingly, the coefficients hardly change as the market size increases. This is because the willingness to pay is identified from product variations within the desktop computer market. This is similar to the logit model where a larger market size is reflected by a larger constant term without changing the characteristics coefficients. A difference is that the hybrid model reflects it with a larger δ_0. However, the market size affects price elasticities and markups in the hybrid model (see the next section.)

Unlike the logit model the hybrid model identifies consumer demand on product characteristics better and implications drawn from estimates are reasonable. Unlike the PCM the hybrid model does not collapse as the market size increases. And the average consumer's willingness to pay for quality improvement is somewhere between those of the PCM and BLP.

Differences in demand estimates among the three models are mainly a result of differences in product quality that each model predicts, i.e., δ_{j_k} in equation (1). In the PCM, the model structure imposes that product quality has the same ranking as price. So a more expensive product is a higher quality product. In the models with the logit error, product quality is highly correlated with market share. So a product with a larger market share is a higher quality product. In the hybrid model price ranks product quality within brands, but brand level quality is highly correlated with market share.

The small cache coefficient is a good example to illustrate this difference. Computers with smaller cache are relatively cheap products but their market shares are larger than similar CPU speed computers with larger cache. In the PCM the small cache coefficient is negative because this attribute makes a product cheaper. It is also negative in the hybrid model because of its vertical structure within brands. In the logit models, on the other hand, it is positive because this attribute makes a product more popular. The random coefficient renders it statistically insignificant, but the sign is still positive.

3.4 Price Elasticity and Markup

Table 4 compares the price elasticity among the three models. The own elasticity in the hybrid model is much higher than that of the logit model and lower than that of the PCM in an absolute term. In the PCM a 1% price decrease induces a share to increase by a factor of 34. This high elasticity is caused by the model structure where all products are lined up on a single dimension and only two products are substitutes to a given product. In the hybrid model a 1% price decrease makes a share increase by a factor of 11. It is still very high but much lower than its counterpart in the PCM. That is because only products of the same brand are lined up on a single dimension in the hybrid model. In the logit model the own elasticity is less than 2 in an absolute term.

One should note that products lined up on the single dimension are very similar products. Two products located right next to each other usually have the same characteristics except for one or two.

The hybrid model distinguishes two types of the cross elasticity: the within-brand elasticity and the between-brand elasticity. The within-brand elasticity is similar to the cross elasticity in the PCM. It is determined by adjacent products of the same brand. Its magnitude in Hybrid I is about a quarter of that of the PCM. The between-brand elasticity is similar to the cross elasticity in the logit model, but only about 10% of products are cross brand substitutes to a given product. The magnitude is also very different. The between-brand elasticity in Hybrid I is larger than its counterpart in the logit model by a factor of 75 and the between-brand elasticity in Hybrid II is by a factor of 36.

Table 5 lists the average markup over time. IV Logit and BLP I have very similar markups, although the average markup in BLP I is lower in all periods. Changing a market size does not change the magnitudes. Other specifications in Table B-2 do not change the markup significantly either. With the log normal distribution on the price coefficient (BLP II in the third column) markups become higher than 1 for all periods and only 36% of products have elastic demand. The average markup in the PCM (the fourth column) is no higher than 0.005 in all periods. It is not surprising considering the PCM's model structure. The model imposes that more than fifty products produced by six brands are vertically differentiated.

In columns 5 to 7 the average markup is reported for the hybrid model with different market sizes. The average markup ranges $0.31 \sim 0.70$ in Hybrid I. When potential consumers are included in Hybrid II, it goes down to $0.15 \sim 0.42$. When more people are included as potential consumers in Hybrid III, it goes down to $0.09 \sim 0.30$. The change is mainly caused by decreasing market shares.

Note that the demand estimates hardly change as the market size increases. The markup is relatively high despite the high own elasticity. Although the own elasticity is high, close substitutes are products of the same brand, so firms can still set price considerably higher than the marginal cost.

Table 6 lists the brand-level average percentage markup, $(p - mc)/p$, based on demand estimates in BLP I, PCM, Hybrid I and Hybrid II. Brands include Apple, Compaq, eMachines, HP, and Sony.[5] HP has the largest market share (39.5 percent), followed by eMachines (25.4 percent)

[5] The data set also includes Gateway computers, but I exclude it from discussion since its products only appear in the last several periods.

and Compaq (24.5 percent). Sony and Apple have small market shares, 9.8 percent and 1.4 percent respectively. Apple computers are the most expensive ones, $1,400 on average. Sony also sells expensive products with the average price around $1,200. eMachines sells the cheapest computers with the average price less than $600. Compaq computers are about $150 more expensive and HP ones are about $300 more expensive than eMachines'.

In BLP I a brand with a higher average price has a lower percentage markup. eMachines has the highest percentage markup, and Apple has the lowest percentage markup. In the single product logit model this is always true. With the magnitude of price much larger than that of market share, a higher price product has a lower percentage markup. This relationship does not necessarily hold true with the random price coefficient, but it does in BLP I.

In the PCM a brand with a higher average price tends to have a higher percentage market. Apple has the highest percentage markup, followed by Sony and HP. This is because consumers at the left end of the distribution buy expensive products in the PCM. They are less elastic consumers than those at the other end. However, Compaq's markup is much lower than eMachines'. This is because Compaq products are squeezed between HP and eMachines products. The "squeezed" product tends to have a low percentage markup in the PCM.

In the hybrid models the average share determines the ranking of the percentage markup at a brand level. The highest is HP, followed by eMachines and Compaq. The lowest is Apple followed by Sony. Note that this is only true at a brand level. The percentage markup has the same pattern as in the PCM within brands. In all three models HP earns the largest variable profit because of its large market share. The ranking among the other brands is similar between BLP I and the two hybrid models, and is mainly determined by the market share. Although Compaq and eMachines have similar markups and market shares, Compaq earns a higher profit because Compaq's price is higher. In the PCM Apple earns the second highest profit, followed by Sony. eMachines earns a slightly lower profit than Sony, and Compaq makes less than a half of eMachines' profit.[6]

3.5 Consumer Welfare

Figure 3 compares the percentage change in consumer welfare. All three models are estimated using the same market size as in the PCM to avoid differences due to market size. There are still other differences among the models. Parameter estimates are different, and the distributional assumption on the price coefficient is also different. In BLP the price coefficient is distributed normal, while it is distributed log normal in the other two models.

With the smaller market size the constant term goes down to -1.67 in BLP. The mean of the price coefficient is -2.26 and the standard deviation is 0.21, but they are not statistically significant. CPU Speed and DVD writer are still the only variables with significant coefficients and their magnitudes are almost the same as in Table 2. The estimates in the hybrid model do not change much either and are almost same as those in Table 3. All estimates are still significant at a 5% level except for the memory coefficient.

Despite all the differences in the model structures and demand estimates, the figure shows similar trends of welfare changes. The direction of changes are the same in 20 periods out of 35. In most periods the magnitude of changes are similar. However, there are a few interesting differences. First, consumer welfare seems to fluctuate more in BLP than in the other two models. The standard deviation is 0.12 in BLP, while it is 0.086 in PCM and 0.074 in the hybrid model. It is mainly due to the product level taste shock in BLP. It is introduced with a new product and goes away with

[6] I ignore Apple's unique position in the market. Apple's operating system is not compatible with that of the other brands and its customers are considered more loyal. Treating it at the same level as the other brands may not be ideal and could be a reason for its small markup.

a product exit. As a result, consumer welfare responds more sensitively to product entry and exit than in the other two models.

Second, BLP and the PCM are similar to each other than to the hybrid model with respect to the direction of changes. The hybrid model has a different sign from the other two in 10 periods. The correlation coefficient is higher between BLP and PCM (0.88) than between the hybrid model and either of the two (0.52 with PCM and 0.51 with BLP.) It may be because the hybrid model treats brand entry/exit differently from product entry and exit. The introduction of a new brand introduces a taste shock but the introduction of a new product does not. The other two models do not distinguish between brand entry and product entry. For example, in March 2004 consumer welfare decreases in both BLP and PCM, but increases in the hybrid model. This is a period when another brand, Gateway, is added in the data but the total number of products decreases.

Lastly, consumer welfare is more sensitive to new product introduction in BLP and the PCM than in the hybrid model. The correlation coefficient between a percentage change in consumer welfare and the number of new products is 0.43 in BLP and 0.33 in the PCM, while it is 0.16 in the hybrid model. A high correlation in BLP is due to the taste shock as explained above. In the PCM it is because a value of the price coefficient (α) for a new product is very small as it is positioned at the left tail of the price coefficient distribution. Therefore, when welfare changes are multiplied by the inverse of the price coefficient, its value increases rapidly with the number of new products. This may also happen in the hybrid model, but it is less severe as the number of products placed under the distribution is much smaller than in the PCM.

4 The Post-Merger Analysis

In this section I show how demand estimates can be used to analyze product repositioning in the post-merger market, using the demand estimates in the hybrid model. The merger between HP and Compaq took place in February 2002, and my sample period is from October 2001 to September 2004. I first examine if the merged firm earned higher profits in the post-merger market. Figure 4 shows the average markup at a brand level recovered from the demand estimation. The figure shows that the markup follows a seasonal cycle. It is the lowest in the second quarter and the highest in the fourth quarter. More interestingly, the figure shows that Compaq's average markup increased while HP's slightly decreased when the same quarters of adjacent periods are compared. eMachines' markup also increased. Combining this with the brand share shown in Figure 1, one may conclude that HP's profit decreased while Compaq's profit increased after the merger.[7]

Considering the fact that Compaq's average price went down, its increased markup means that its marginal cost went down further than the price. So one may speculate that only Compaq enjoyed the efficiency gain from the merger so much that its markup increases even with the declining price. Although I do not rule out this possibility, it is also possible that changes in the marginal cost are associated with changes in product characteristics. In other words, Compaq and HP may have become more differentiated from each other after the merger by repositioning their products.

In order to explore this possibility further I construct a quality index for each brand based on the demand estimates in the following way. I first compute the average value of all observed characteristics for each brand. They include CPU speed, CPU type (Intel, AMD, or Apple),

[7] This asymmetry rules out factors affecting the whole PC industry as explanations.

memory capacity, hard drive capacity, the size of the level 2 cache, the screen size, whether the screen is LCD, whether the DVD reader is included, and whether the DVD writer is included. I use the simple average, instead of the sale weighted average, in order to reflect product characteristics that the firms offer, not characteristics that consumers choose. Then for brand j, the index is constructed by

$$q_j = \sum_{k=1}^{K} \widehat{\beta}_k \overline{x}_{jk}, \tag{11}$$

where $\overline{x}_{jk}$ is brand j's average value of characteristic k and $\widehat{\beta}_k$ is its estimated marginal utility in the demand model. Having a correct sign for $\widehat{\beta}_k$ is important in correctly projecting products on characteristics space.

Figure 5 shows the quality index during the sample period. Apple's index is highest, followed by Sony and HP. The gap between Apple and Sony becomes narrower towards the end of the sample period. eMachines' index is the lowest. This ranking is consistent with the price ranking. The figure shows that Compaq and HP diverge over time. HP's index keeps up with those of Sony and Apple. On the other hand, Compaq's index becomes closer to that of eMachines and from August 2003 the two brands follow almost the same path. This suggests that the merged firm repositioned its two brands over time and that Compaq's increased markup is an outcome of this product repositioning rather than the asymmetric efficiency gain or less competitive market structure.

I formally test if there are breaks in the trends using the Quandt Likelihood Ratio (QLR) test with 15% trimming. The regression is

$$y_{kt} = \alpha_k + \beta_k y_{kt-1} + \gamma_0 D_t(\tau_r) + \gamma_1 [D_t(\tau_r) \times y_{t-1}] + \varepsilon_t,$$

where y_{kt} is the quality index of brand k at period t and $\varepsilon_t \sim N\left(0, \sigma^2\right)$. τ_r denotes the hypothesized break point and $D_t\left(\tau_r\right)$ is a dummy variable that equals zero before τ_r and one after. With 15 percent trimming I test for breaks at all months between April 2002 and April 2004. Unfortunately, the first period that can be tested for a break is two months after the merger. Thus if the divergence between HP and Compaq had started sometime before or right after the merger, this test misses the starting period.

This test result shows that Compaq's largest break is in October 2002 and HP's largest one is in September 2002. However, both breaks are not statistically significant at a 10 percent significant level with 15 percent trimming. This result suggests that the divergence started around the merger so that the two brands' trends were already on different paths in the sample period. The QLR test is applied to the other brands as well. Sony's largest break is in July 2002 and Apple's largest break is in September 2003, but both breaks are not significant at a 10 percent significant level. Moreover, Apple's largest break is about a year after the other brands' breaks. However, eMachines' quality index shows a significant break in November 2002. The QLR statistics is 10.21. This suggests that eMachines responded to the merging firm's product repositioning by repositioning its own products.

This finding is not consistent with a standard merger analysis that predicts the merged firm will increase price to exploit a less competitive market and thus consumer welfare decreases. Therefore, a merger can only be justified if the supply side efficiency gain is larger than a loss in consumer welfare. For example, Nevo (2000) computes a welfare loss on the consumer side from hypothetical mergers in the ready-to-eat cereal market, and estimates the supply side efficiency gain that justifies these mergers.

Recently, researchers pay more attention to product repositioning in a post-merger market.

They argue that the merged firm may have an incentive to change product characteristics or withdraw duplicative products to avoid carnibalization. For example, Gandhi, Froeb, Tschanz and Werden (2008) provide a theoretical model of product repositioning. In their model firms change both price and location simultaneously and instantly after the merger. They show that the merged firm moves its products away from each other to reduce carnibalization. The merged firm's incentive to raise prices is reduced by this repositioning, and the anticompetitive merger effects are mitigated as a result. Although I do not formally model a relationship between the merger and product positioning, my finding is consistent with the theoretical prediction in Gandhi et.al. (2008).[8]

5 Conclusions

In this paper I consider the hybrid discrete choice model of differentiated product demand that combines the PCM and BLP. Consumers in this model receive an idiosyncratic taste shock only at a brand-level so that it does not affect their product choice within brands. As a result, the model maintains horizontal differentiation at a brand-level while allowing products to be vertically differentiated within brands. With the distinguished two types of differentiation a product has more substitutes than in the PCM, but fewer substitutes than in BLP.

The empirical results show that the hybrid model performs better than BLP and the PCM in estimating PC demand. The willingness to pay for product characteristics improvement is statistically significant and its magnitude is more reasonable. The estimated brand-level markup reflects the average quality difference among brands as well as their market dominance. All three

[8] See Berry and Waldfogel (2001) for empirical evidence on product repositioning in a post-merger market.

models have similar trends of percentage change in consumer welfare over time, but it is less volatile in the hybrid model. This is because the hybrid model treats brand entry/exit differently from product entry/exit.

The post-merger analysis shows that Compaq's profit increased while HP's profit decreased after the merger. I argue that this asymmetry is an outcome of the product repositioning, and show that the two brands were differentiated further from each other after the merger.

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Table 1: Trends in the Desktop Personal Computer Market from 4Q2001 to 3Q2004

	Price (in dollars)				Quantity (in thousands)				CPU speed (in GHz)			
Time	mean	std	min	max	mean	std	min	max	mean	std	min	max
4Q01	825.88	255.78	445.50	1,936.92	13.55	19.08	1.01	175.31	1.29	0.26	0.50	2.00
1Q02	827.45	259.00	350.38	2,081.72	9.51	9.90	1.03	54.09	1.35	0.26	0.60	2.20
2Q02	788.99	240.12	421.21	1,878.22	6.34	5.75	1.05	32.10	1.43	0.28	0.70	2.26
3Q02	795.12	252.50	393.65	1,987.81	6.42	6.38	1.00	29.17	1.60	0.35	0.70	2.53
4Q02	739.19	253.96	388.62	1,988.93	10.03	13.87	1.03	156.90	1.91	0.37	0.70	2.66
1Q03	718.78	291.42	360.04	2,265.47	7.15	7.43	1.00	32.67	1.97	0.36	0.70	3.06
2Q03	733.54	307.05	355.55	2,074.25	6.84	5.79	1.00	37.50	2.15	0.33	0.80	3.06
3Q03	710.00	299.60	343.41	2,073.72	7.17	9.25	1.00	57.58	2.26	0.31	1.00	3.00
4Q03	724.18	295.39	373.02	2,169.56	9.89	13.79	1.04	149.49	2.46	0.31	1.00	3.20
1Q04	729.75	289.46	322.21	2,147.68	7.15	8.49	1.01	55.13	2.55	0.33	1.00	3.20
2Q04	707.41	271.81	357.77	2,132.67	6.33	6.60	1.00	30.75	2.53	0.37	1.00	3.40
3Q04	690.64	248.03	222.14	1,699.68	7.27	7.76	1.07	44.57	2.48	0.34	1.25	3.40

Table 2: Demand Estimates of Other Discrete Choice Models

Variable	Logit	IV Logit	BLP I†	BLP II‡	PCM
Constant	-5.889*	-4.488*	-4.216*	-5.821*	1.156*
	(0.238)	(0.951)	(1.831)	(0.291)	(0.059)
CPU Speed	0.611*	0.873*	0.875*	0.634*	0.065*
	(0.115)	(0.205)	(0.219)	(0.139)	(0.009)
Memory	-0.014	0.003	0.006	-0.016	0.006*
	(0.021)	(0.023)	(0.030)	(0.020)	(0.001)
Hard Drive	0.093	0.363	0.380	0.109	0.035*
	(0.096)	(0.195)	(0.235)	(0.105)	(0.009)
Intel CPU	-0.340	-1.164	-1.155	-0.374	-0.167*
	(0.415)	(0.602)	(0.653)	(0.408)	(0.022)
AMD CPU	0.112	-0.801	-0.815	0.097	-0.181*
	(0.404)	(0.656)	(0.722)	(0.395)	(0.027)
Small Cache	0.358*	0.165	0.116	0.367*	-0.087*
	(0.076)	(0.156)	(0.311)	(0.071)	(0.009)
Screen Size	-0.004	0.005	0.007	-0.003	0.003*
	(0.004)	(0.007)	(0.011)	(0.004)	(0.0004)
LCD Screen	0.003	0.331	0.336	0.011	0.032*
	(0.095)	(0.234)	(0.256)	(0.131)	(0.012)
DVD Reader	-0.030	0.021	0.042	-0.031	0.050*
	(0.065)	(0.077)	(0.138)	(0.067)	(0.004)
DVD Writer	0.242*	0.485*	0.507*	0.249*	0.064*
	(0.101)	(0.193)	(0.238)	(0.111)	(0.010)
Price_mu	-0.944*	-2.228*	-2.751	0	0
	(0.126)	(0.855)	(2.997)		
Price_sigma	0	0	0.683	0.059	1.243*
			(1.912)	(5.899)	(0.191)

The firm dummy variables and the time dummy variables are included.

*significant at a 5% level.

†The price variable has a random coefficient that is distributed normal.

‡The price variable has a random coefficient that is distributed log normal.

Table 3: Demand Estimates in the Hybrid Demand Model

Variable	Hybrid I[†]	Hybrid II[‡]	Hybrid III[♯]	Hybrid IV[ℸ]
Constant	0.528*	0.525*	0.521*	0.517*
	(0.076)	(0.070)	(0.073)	(0.073)
CPU Speed	0.135*	0.124*	0.123*	0.122*
	(0.059)	(0.020)	(0.020)	(0.020)
Memory	0.006	0.007	0.007*	0.007*
	(0.005)	(0.004)	(0.004)	(0.004)
Hard Drive	0.102*	0.103*	0.102*	0.101*
	(0.022)	(0.017)	(0.018)	(0.019)
Intel CPU	-0.391*	-0.378*	-0.376*	-0.374*
	(0.081)	(0.052)	(0.055)	(0.058)
AMD CPU	-0.439*	-0.432*	-0.429*	-0.427*
	(0.060)	(0.052)	(0.056)	(0.058)
Small Cache	-0.133*	-0.134*	-0.134*	-0.133*
	(0.018)	(0.012)	(0.012)	(0.012)
Screen Size	0.007*	0.007*	0.007*	0.007*
	(0.001)	(0.001)	(0.001)	(0.001)
LCD Screen	0.092*	0.092*	0.091*	0.090*
	(0.027)	(0.026)	(0.027)	(0.027)
DVD Reader	0.060*	0.060*	0.060*	0.060*
	(0.010)	(0.010)	(0.010)	(0.010)
DVD Writer	0.139*	0.139*	0.139*	0.138*
	(0.020)	(0.018)	(0.018)	(0.018)
Price_mu	0	0	0	0
Price_sigma	0.406*	0.407*	0.413*	0.417*
	(0.109)	(0.099)	(0.104)	(0.105)

The firm dummy variables and the time dummy variables are included.

[*]significant at a 5% level.

[†]The market is defined as the US household desktop computer market and its size is estimated based on the number of computers sold to household consumers. There are two outside options. One is to buy a product that belongs to one of the six brands but does not appear in the sample, and the other is to buy Dell products. The value of the first outside option is set to zero, and the value of the second is estimated along with other estimates.

[‡]The market includes potential consumers and its size is set to three millions. Not buying anything is included as another outside option.

[♯]The market is defined in the same way as in Hybrid II, but its size is set to five millions.

[ℸ]The market is defined in the same way as in Hybrid II, but its size is set to ten millions.

Table 4: Median of Price Elasticity in Different Demand Models

	IV Logit	BLP I	PCM	Hybrid I	Hybrid II
Own elasticity	-1.74	-1.88	-3,368.2	-1,136.4	-2,519.0
Cross elasticity					
Within-brand	0.00048	0.00041	1,946.1	489.83	1,096.0
Between-brand	0.00047	0.00036	1,453.4	0.0351	0.0170
A ratio of substitutes across brands†	1	1	0.03	0.10	0.10

See Tables 2 and 3 for estimates in different demand models.
The medians of each period are averaged over all periods.
†The mean ratio of other brand products that are substitutes to a given brand product.

Table 5: The Average Percentage Markups in Different Demand Models

	IV Logit	BLP I	BLP II	PCM	Hybrid I	Hybrid II	Hybrid III
4Q01	0.553	0.514	1.275	0.0025	0.404	0.232	0.152
1Q02	0.571	0.528	1.311	0.0029	0.378	0.220	0.143
2Q02	0.566	0.526	1.282	0.0037	0.351	0.145	0.092
3Q02	0.588	0.543	1.338	0.0032	0.375	0.165	0.105
4Q02	0.633	0.576	1.455	0.0036	0.696	0.417	0.300
1Q03	0.639	0.587	1.467	0.0026	0.353	0.170	0.108
2Q03	0.612	0.574	1.422	0.0031	0.392	0.149	0.094
3Q03	0.628	0.572	1.427	0.0018	0.334	0.172	0.110
4Q03	0.608	0.555	1.393	0.0033	0.316	0.221	0.143
1Q04	0.614	0.562	1.401	0.0019	0.358	0.210	0.135
2Q04	0.639	0.583	1.450	0.0019	0.399	0.187	0.119
3Q04	0.674	0.610	1.544	0.0033	0.401	0.252	0.163

See Tables 2 and 3 for estimates in different demand models.

Table 6: The Average Percentage Markup by Brands

	BLP I	PCM	Hybrid I	Hybrid II
Apple	0.354	0.0215	0.133	0.070
Compaq	0.609	0.0007	0.332	0.166
eMachines	0.723	0.0019	0.366	0.181
HP	0.527	0.0020	0.531	0.296
Sony	0.398	0.0031	0.195	0.099

See Tables 2 and 3 for estimates in different demand models.

Figure 1: The Market Share by Brand from October 2001 to September 2004

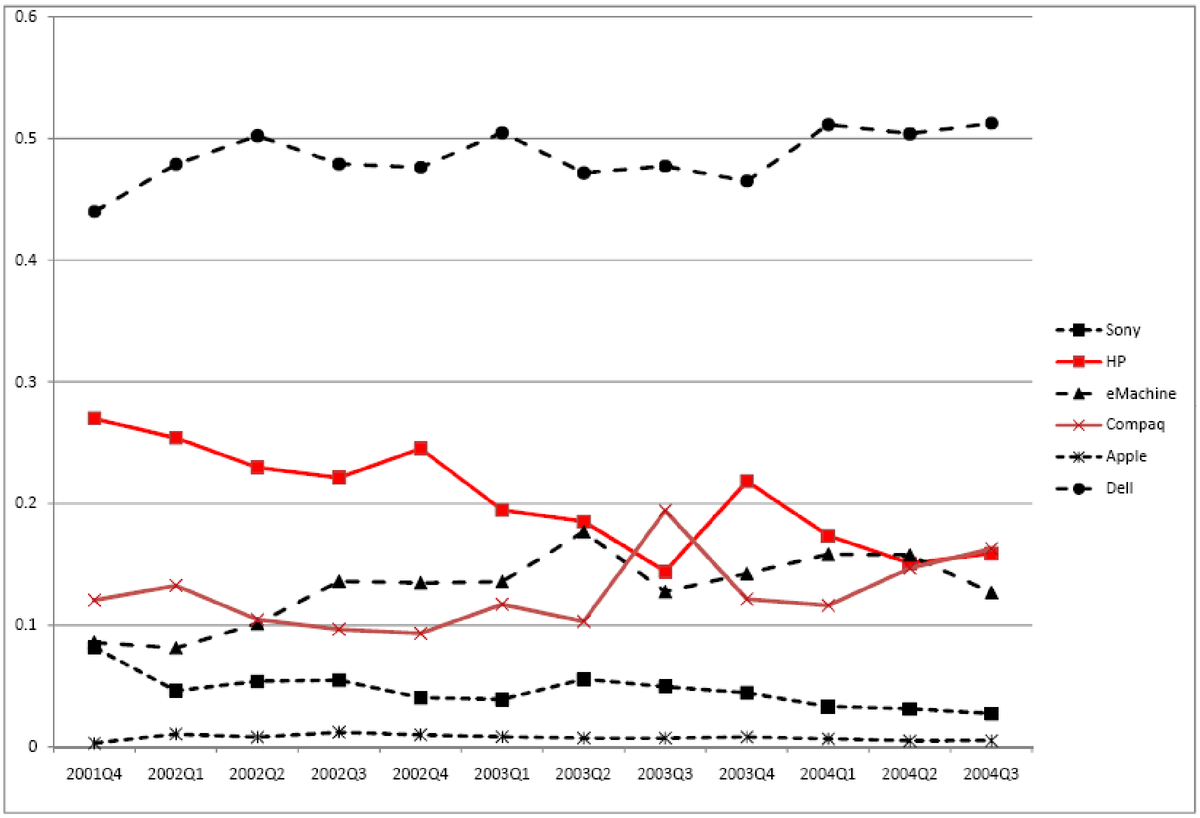


Figure 2: The Average Price by Brand from October 2001 to September 2004

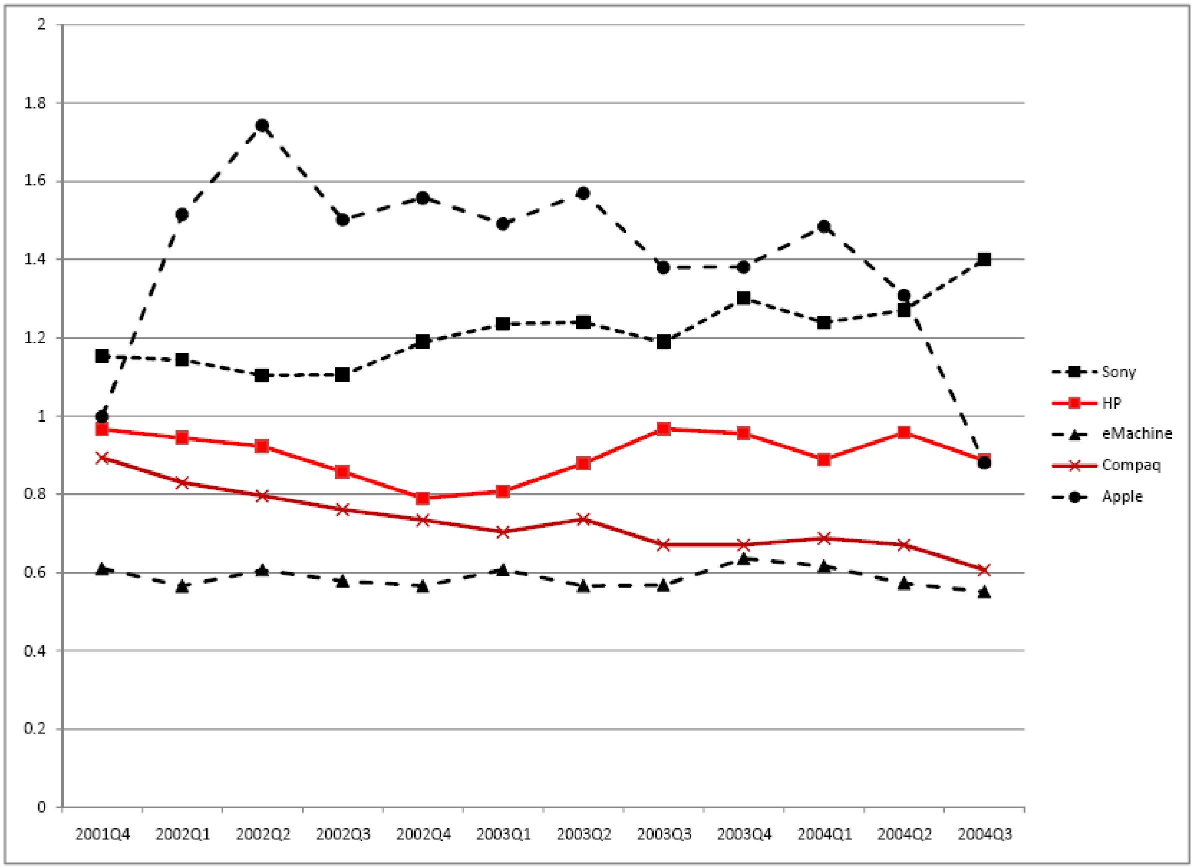


Figure 3: Consumer Welfare from October 2001 to September 2004

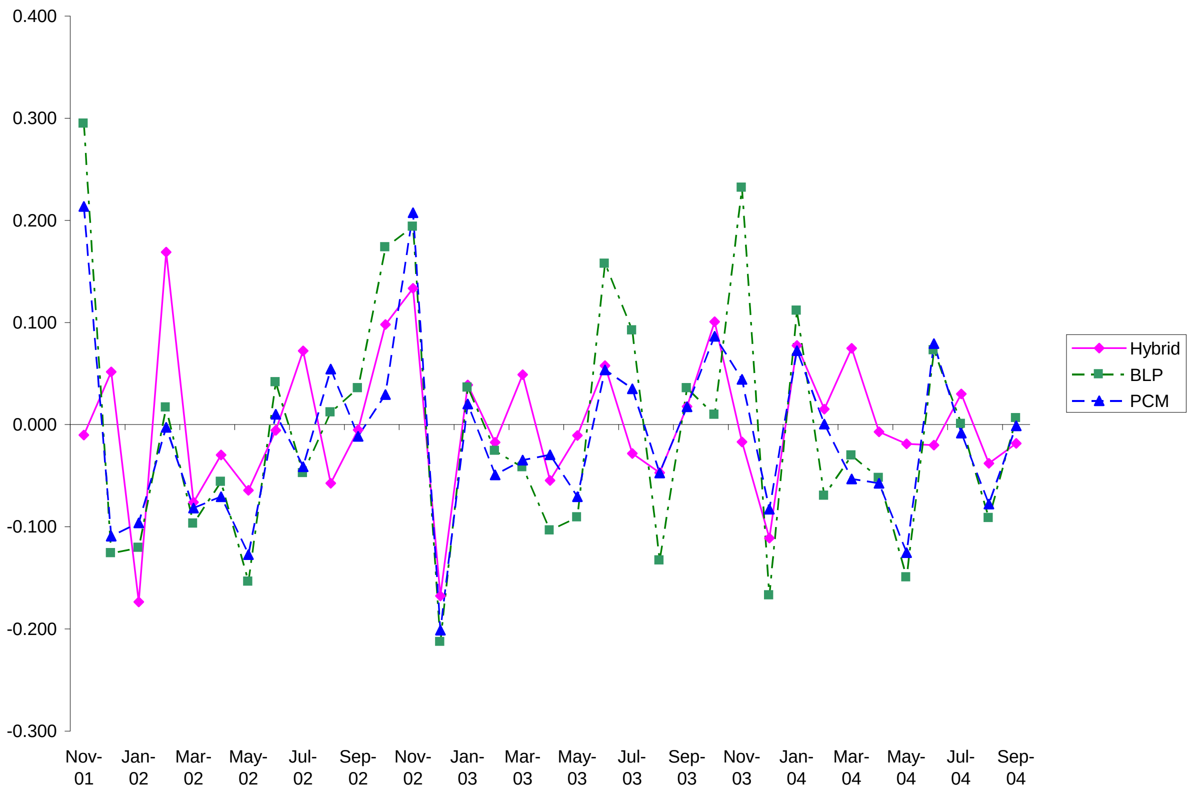


Figure 4: The Average Markup by Brand from October 2001 to September 2004

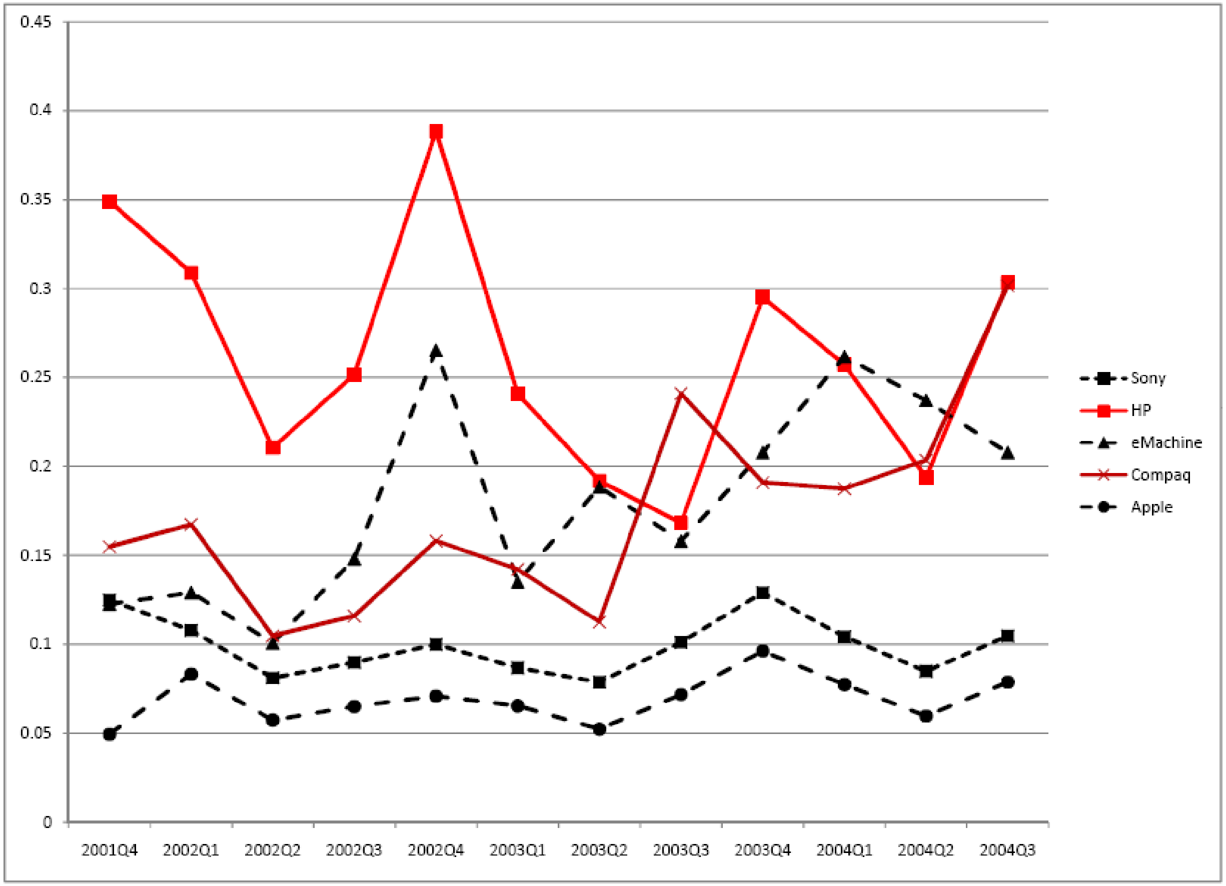
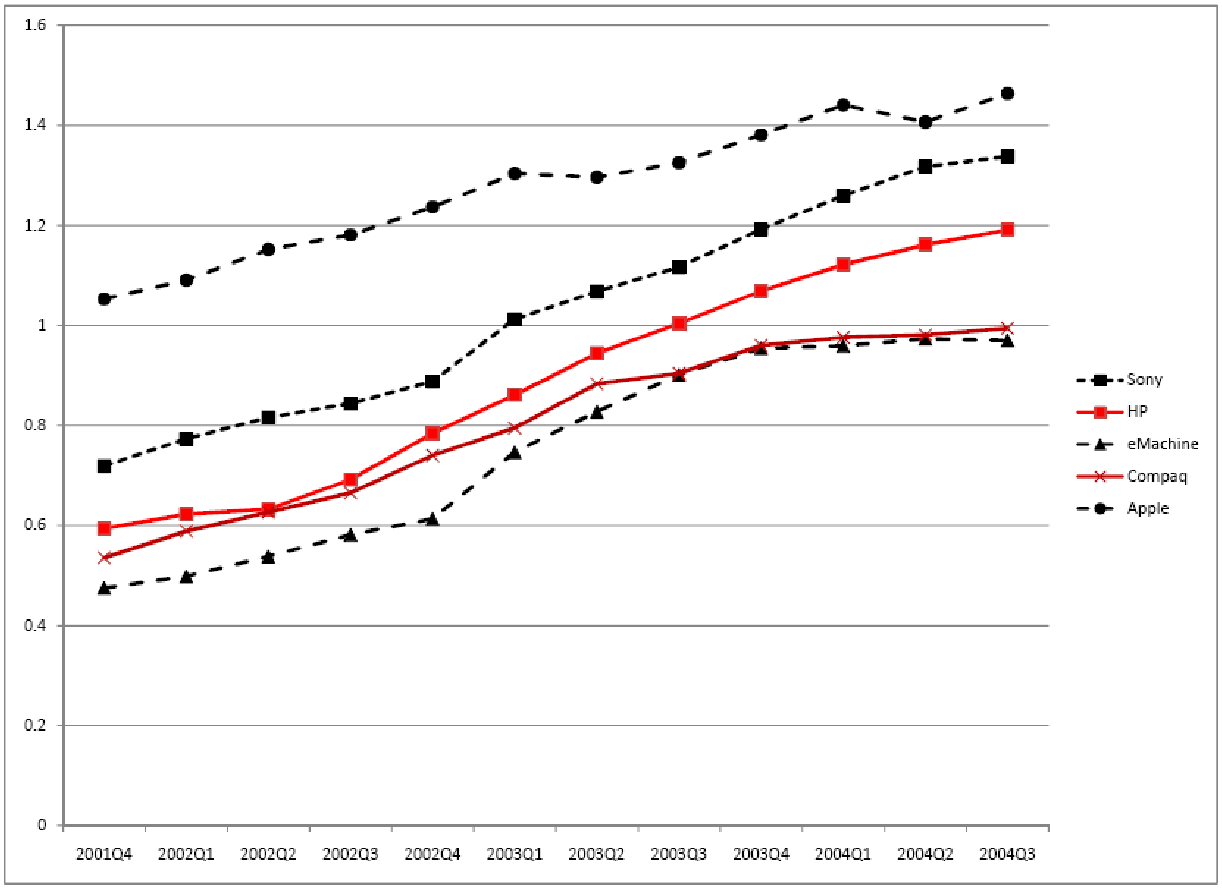


Figure 5: The Quality Index from October 2001 to September 2004



Appendix A: Data Description

Scanner data on PCs were collected from the US retail outlets by NPD Techworld.[9] The original data set contains 6,235 computer products ranging from PDAs to desktops and has 47,923 observations for 36 months from October of 2001 to September of 2004. The data set mainly consists of the desktop and notebook computers. There are 2,769 desktop and 2,756 notebook computers with 66% and 33% of the total sale respectively. The rest consists of small portable computers like tablet PCs and subnotes. Products of Dell are not included in the data set since it does not sell products at retail outlets.

IDC estimates that about 47.6 millions of computers were sold in the US in 2002 and 52.7 millions in 2003.[10] And about 17.1 millions were sold to household consumers in 2002 and about 20 millions in 2003. The total unit sold in the data set is 7.7 and 8.4 millions in 2002 and 2003 respectively, which means that the data set covers about $42 \sim 45\%$ of the US household market. Since products of Dell, which has about 30% market share in the US market, are not included, the data set covers $60 \sim 65\%$ of the US retail outlet market.[11]

Most observations have very small sales. 53.95% of the total observations have less than 10 units of sale, 78.64% less than 100 units, and 90% less than 1,000 units. However, the sale is concentrated on a small number of products. Observations with more than 100 units cover about 96% of the total sale and observations with more than 1,000 units cover about 90% of the sale. This means that 10% of observations cover 90% of the total sale. Moreover, when observations with less than 100 units are excluded, all of outliers in price and product characteristics disappear. And the summary statistics of product characteristics do not change significantly when a cutoff is raised to 1,000 units.

Appendix B: Demand Estimation in the Random Coefficient Logit Model (BLP)

In Table B-1 I report the IV logit estimation with different instrumental variables. The table shows that the price coefficient becomes positive with the BLP-type IVs (IV 1). When product characteristics are interacted with the time dummy variables, the price coefficient becomes negative. This is probably because the price does not increase over time with improving product characteristics. IV 4 is used to estimate BLP in Section 5.

In Tables B-2 and B-3 I report BLP estimates with different specifications. In Table B-2 variations of BLP I in Table 2 are reported. The random coefficients are added on the constant term and the speed variable in addition to the price variable, but they do not improve model identifications. In Table B-3 variations of BLP II in Table 2 are reported. Different parameters are normalized and different instrumental variables are used for each specification, but the identification does not improve.

[9] The same data are used in Aizcorbe and Pho (??) and Kokoski et. al. (2000) where more details on the data can be found.

[10] Gartner estimates that 43.9 millions were sold in 2002 and 57.7 millions were sold in 2003.

[11] Gartner estimates that the market share of Dell in the US market is 29.69% in 2002 and 28.19% in 2003.

Table A-1: Summary Statistics of Product Characteristics

	Memory (in Mega bytes)				Hard Drive (in Giga bytes)				Screen Size (in inches)			
	mean	std	min	max	mean	std	min	max	mean	std	min	max
4Q01	232.78	131.00	64	512	42.29	18.03	20	80	16.90	0.35	15	17
1Q02	312.66	157.13	64	512	53.30	24.78	20	120	16.36	0.83	15	17
2Q02	239.29	141.12	64	512	50.36	21.28	20	120	16.50	0.84	15	17
3Q02	291.94	174.22	64	512	53.57	19.91	20	120	16.65	0.72	15	17
4Q02	306.26	157.01	128	512	63.16	23.03	20	120	16.51	0.80	15	17
1Q03	306.21	160.91	128	1024	64.83	26.45	40	250	16.27	0.96	15	18
2Q03	344.38	152.09	128	1024	74.31	30.51	40	160	16.18	0.86	15	17
3Q03	323.26	164.24	128	1024	79.17	33.01	40	160	16.45	0.89	15	17
4Q03	366.83	139.04	128	1024	88.32	39.17	40	200	16.63	0.80	15	20
1Q04	395.06	129.20	128	1024	99.97	47.95	40	250	16.68	0.82	15	20
2Q04	460.10	116.57	256	1024	111.76	52.66	40	250	16.83	0.60	15	20
3Q04	445.36	143.47	256	1024	113.17	56.84	40	250	16.90	0.47	15	19

Table A-2: Summary Statistics of Product Characteristics*

	Intel CPU	AMD CPU	Cache†	Screen‡	LCD screen	DVD reader	DVD writer
4Q01	0.82	0.18	0.463	0.106	0.000	0.514	0.021
1Q02	0.85	0.13	0.516	0.136	0.012	0.533	0.036
2Q02	0.78	0.20	0.452	0.073	0.014	0.526	0.041
3Q02	0.75	0.23	0.493	0.144	0.016	0.592	0.075
4Q02	0.78	0.20	0.473	0.242	0.019	0.587	0.118
1Q03	0.57	0.42	0.284	0.194	0.025	0.764	0.162
2Q03	0.58	0.41	0.277	0.217	0.051	0.745	0.216
3Q03	0.53	0.46	0.285	0.321	0.098	0.700	0.220
4Q03	0.70	0.29	0.458	0.317	0.120	0.709	0.234
1Q04	0.71	0.28	0.478	0.343	0.148	0.700	0.297
2Q04	0.58	0.41	0.408	0.233	0.046	0.821	0.422
3Q04	0.61	0.38	0.414	0.252	0.022	0.927	0.439

*Proportions of products with relevant attributes
†A proportion of products with a smaller cache size than the standard size.
‡A proportion of products with a screen included.

Table B-1: Demand Estimates in the IV Logit Model

Variable	Simple Logit	IV 1†	IV 2‡	IV 3◇	IV 4⊤
Constant	-5.889*	-9.927*	-5.498*	-4.722*	-4.488*
	(0.238)	(1.711)	(0.735)	(0.916)	(0.951)
CPU Speed	0.611*	-0.115	0.565*	0.828*	0.873*
	(0.115)	(0.342)	(0.162)	(0.198)	(0.205)
Memory	-0.014	-0.069	-0.005	-0.001	0.003
	(0.021)	(0.037)	(0.022)	(0.023)	(0.023)
Hard Drive	0.093	-0.658	0.149	0.318	0.363
	(0.096)	(0.338)	(0.157)	(0.189)	(0.195)
Intel CPU	-0.340	1.973	-0.446	-1.016	-1.164
	(0.415)	(1.049)	(0.469)	(0.582)	(0.602)
AMD CPU	0.112	2.721	-0.058	-0.637	-0.801
	(0.404)	(1.155)	(0.504)	(0.633)	(0.656)
Small Cache	0.358*	0.953*	0.310*	0.199	0.165
	(0.076)	(0.268)	(0.128)	(0.151)	(0.156)
Screen Size	-0.004	-0.030*	-0.004	0.004	0.005
	(0.004)	(0.012)	(0.006)	(0.007)	(0.007)
LCD Screen	0.003	-0.941*	0.102	0.277	0.331
	(0.095)	(0.415)	(0.187)	(0.227)	(0.234)
DVD Reader	-0.030	-0.191	-0.010	0.014	0.021
	(0.065)	(0.102)	(0.070)	(0.076)	(0.077)
DVD Writer	0.242*	-0.491	0.325*	0.446*	0.485*
	(0.101)	(0.328)	(0.158)	(0.188)	(0.193)
Price	-0.944*	2.759	-1.245	-2.012*	-2.228*
	(0.126)	(1.575)	(0.656)	(0.824)	(0.855)
Validity of IVs		Yes	Yes	Yes	Yes

†IV 1: BLP IVs. Characteristics used are CPU Speed, Memory, Hard Drive, Screen Size, and DVD Writer

‡IV 2: CPU Speed variable interacted with time dummy variables

◇IV 3: BLP IVs interacted with time dummy variables

⊤IV 4: BLP IVs interacted with time dummy variables excluding Hard Drive and DVD Writer variables.

All specifications include dummy variables for firm and time.

Table B-2: Demand Estimates in the Random Coefficient Logit Model with $\alpha_i \sim N(\mu_\alpha, \sigma_\alpha)$ and $\beta_i \sim N(\mu_\beta, \sigma_\beta)$

Variable	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Means				
Constant	-4.216*	-5.660	-3.925*	-4.318*
	(1.831)	(30.606)	(1.928)	(13.357)
CPU Speed	0.875*	0.872*	0.869	0.878
	(0.219)	(0.218)	(1.102)	(0.961)
Memory	0.006	0.006	0.008	0.007
	(0.030)	(0.028)	(0.030)	(0.030)
Hard Drive	0.380	0.373	0.394	0.390
	(0.235)	(0.240)	(0.243)	(0.240)
Intel CPU	-1.155	-1.135	-1.119	-1.154
	(0.653)	(0.661)	(0.941)	(0.794)
AMD CPU	-0.815	-0.797	-0.801	-0.829
	(0.722)	(0.719)	(0.960)	(0.856)
Small Cache	0.116	0.110	0.068	0.082
	(0.311)	(0.268)	(0.297)	(0.280)
Screen Size	0.007	0.007	0.008	0.008
	(0.011)	(0.010)	(0.010)	(0.010)
LCD Screen	0.336	0.327	0.330	0.341
	(0.256)	(0.266)	(0.261)	(0.259)
DVD Reader	0.042	0.047	0.063	0.058
	(0.138)	(0.128)	(0.137)	(0.129)
DVD Writer	0.507*	0.506*	0.520*	0.523*
	(0.238)	(0.221)	(0.222)	(0.239)
Price	-2.751	-2.702	-3.322	-3.065
	(2.997)	(2.733)	(2.844)	(3.107)
Standard Deviations				
Constant	0	2.327	0	0.945
		(31.218)		(21.344)
Price	0.683	0.749	1.039	0.901
	(1.912)	(1.495)	(1.467)	(1.351)
CPU Speed	0	0	0.036	0.031
			(8.496)	(9.592)

Five thousand simulated consumers are drawn from the standard normal distribution to compute the model predicted market shares.

Table B-3: Demand Estimates in the Random Coefficient Logit Model with $\log(\alpha_i) \sim N(\mu, \sigma)$

Variable	IV 2†		IV 4‡	
	Spec. 1	Spec. 2	Spec. 1	Spec. 2
Constant	-5.772*	-6.501*	-5.821*	-2.855
	(0.226)	(1.160)	(0.291)	(1.900)
CPU Speed	0.508*	0.385*	0.634*	0.825*
	(0.150)	(0.178)	(0.139)	(0.207)
Memory	-0.009	-0.018	-0.016	0.011
	(0.020)	(0.025)	(0.020)	(0.028)
Hard Drive	0.089	-0.051	0.109	0.365
	(0.126)	(0.184)	(0.105)	(0.217)
Intel CPU	-0.262	0.130	-0.374	-1.002
	(0.437)	(0.523)	(0.408)	(0.621)
AMD CPU	0.149	0.599	0.097	-0.673
	(0.436)	(0.579)	(0.395)	(0.693)
Small Cache	0.352*	0.462*	0.367*	0.051
	(0.073)	(0.173)	(0.071)	(0.226)
Screen Size	-0.006	-0.011	-0.003	0.008
	(0.004)	(0.007)	(0.004)	(0.009)
LCD Screen	0.015	-0.154	0.011	0.275
	(0.163)	(0.212)	(0.131)	(0.234)
DVD Reader	-0.019	-0.042	-0.031	0.089
	(0.068)	(0.081)	(0.067)	(0.102)
DVD Writer	0.262*	0.136	0.249*	0.508*
	(0.121)	(0.190)	(0.111)	(0.218)
Price (μ)	0	-1.422	0	2.115*
		(3.949)		(0.744)
Price (σ)	0.381	1	0.059	1
	(1.456)		(5.899)	

Two thousand simulated consumers are drawn from the standard normal distribution to compute the model predicted market shares.

†CPU Speed is interacted with time dummy variables.

‡BLP IVs are interacted with time dummy variables.